AGRICULTURAL SHOCKS AND RIOTS: A DISAGGREGATED ANALYSIS

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Agricultural shocks and riots: a disaggregated analysis*

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Abstract

Every year, riots cause a substantial number of fatalities in less-advanced countries. This paper explores the role of agricultural output shocks in explaining riots. Our theory predicts a negative relationship between the level of rioting and the deviation of the actual output from the average one. Relying on monthly data at the cell level (0.5×0.5 degrees), and using a drought index to proxy for output shocks, our empirical analysis confirms such a negative relationship for Sub-Saharan Africa: A one-standard-deviation decrease in the drought index rises the likelihood of a riot in a given cell and month by 8.4 percent. The use of highly disaggregated data accounts for the fact that riots are temporally and geographically confined events.

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1 Introduction

Over the past decade, understanding the determinants of internal conflict has become a central concern for academics and policy makers alike (see, e.g., Blattman and Miguel, 2010, for a detailed overview). So far, the literature has mostly focused on internal conflict between organized groups, for example on coups, rebellions, or revolutions.[1] Little attention has been paid, however, to other manifestations of internal conflict, in particular to riots. Contrary to coups, rebellions, or revolutions—where a potentially persistent fight occurs between at least two organized groups over the control of the state—riots are a violent and punctual disturbance to the public order by a crowd of individuals, for instance with the aim to show disaffection towards government decisions or to oppose specific government actions; hence they flare up spontaneously and tend to die down quickly.

This paper looks at the economic causes of rioting. Doing so is important for a variety of reasons. For one, riots are often associated with a very high number of fatalities. According to the *New York Times* ("U.N. Raises Concerns as Global Food Prices Jump", September 4, 2010), two days of rioting in Mozambique in August 2010 left ten people dead and some 300 injured. About two years earlier, a wave of "food riots" in Africa claimed many more lives (24-100 in Cameroon alone, according to a guess by Berazneva and Lee, 2013). Looking at our data, which covers Sub-Saharan Africa in the period from 1990 to 2012,[2] we observe at least one fatality in about 52% of the cases, with a median of 6 and an average of 66 deaths per event. Overall, in our dataset, there are 1,738 events of rioting and the associated total number of fatalities is 60,170. Of course, next to the cost in terms of human lives, rioting is also costly in economic terms. Riots disrupt private economic activity and basic government functions; as a result, frequent rioting is a severe

[1] Coups and rebellions are attempts by the armed forces (coup) or by an organized group of civilians (rebellion) to oust the incumbent government. Revolutions, on the other hand, may also lead to a fundamental change in political institutions. According to the usual (but not uncontested) definition, a conflict between organized groups is called a "civil conflict" if it causes at least 25 battle death in a single year and it is called a "civil war" if this number is greater than 1000 (see Blattman and Miguel, 2010).

[2] In our empirical analysis, we use data from 1990–2011 as our main explanatory variable is only available until 2011.

obstacle to economic development, particularly in poor places.[3]

A further reason for focusing on riots is that, according to conventional wisdom, rebellions or revolutions rarely start all of a sudden but are often preceded by a series of protests and riots (see, e.g., Labrousse, 1969, for a detailed account of how the food riots of 1789, 1830 and 1848 in France turned into bigger conflicts). Thus, a better grasp of the triggers of riots may lead to a better understanding of the emergence of truly disruptive events like rebellions or revolutions. Against this background, the present paper offers two main contributions. *First*, we develop a simple theoretical framework of rioting. The framework, which also highlights the difference between riots and other forms of internal conflicts (like coups, rebellions, or revolutions), makes a clear prediction as to how the level of rioting in a region is related to the region's current economic situation. *Second*, guided by our theoretical framework, we empirically investigate the relationship between the level of rioting and current economic circumstances, thereby relying on geographically and temporally disaggregated data from Sub-Saharan Africa.

Our theoretical framework is a rational rioting model in which rioting is used by inhabitants of a certain region of a country (the "citizens") to oppose decisions of a superior level of government (the "central government"). In particular, we assume that the central government tries to tax the citizens, while the latter can resort to rioting to resist taxation. This setup gives rise to a simple Markovian equilibrium in which we observe high levels of rioting when the current regional output is below the normal output, while there is little rioting when output is above normal. The intuition is that the government does not observe the current output level, but only past ones, and hence must base its taxation decision on expectations. If the regional economy used to operate above normal in the previous period, expected current incomes are high—which induces the government to announce high taxes: If incomes are high, rioting comes at a substantial opportunity cost, thereby muting the citizens' response to taxation. Yet, if incomes—and hence opportunity costs—turn out to be lower than expected due to a fall in output,

[3]For anecdotal evidence, see the *Economist* article "A cracked nation holds its breath" (January 17, 2008) which describes how the riots that erupted in Kenya in late 2007 imperiled the country's economy.

rioting intensifies. In response, the government lowers taxes to calm down the situation.[4]

Our empirical analysis covers the 1990-2011 period and is based on a geographically and temporally disaggregated approach. In our case, geographically disaggregated means that we take as units of observation subnational cells of 0.5×0.5 degrees. Temporally disaggregated, on the other hand, refers to the fact that we focus on monthly observations. Studying riots, it appears natural to consider short sub-annual periods: Riots flare up spontaneously and tend to die down quickly (in our sample, 91% do not last longer than a week).[5] Using geo-referenced data from the Social Conflict in Africa Database (SCAD), our prime measure of social unrest in a given cell/month is the number of days with riots. Since income data is not available at this high level of spatial/temporal resolution, we follow a reduced-form approach (as do, e.g., Harari and La Ferrara, 2013; Couttenier and Soubeyran, 2014) to explore how social unrest is affected by current economic conditions. Our main explanatory variable is the Standardized Precipitation-Evapotranspiration Index (SPEI) constructed by Vicente-Serrano et al. (2010). As the name implies, SPEI is a drought index reflecting the climatic water balance, i.e., the monthly difference between precipitation and potential evapotranspiration. SPEI is expressed in units of standard deviations from the long-run average, so that a positive (negative) value in a given month means an above (below) normal water balance. The water balance matters primarily for vegetation activity: A lower balance reduces plant growth (Vicente-Serrano et al., 2012) and hence agricultural output. The SPEI can therefore be taken as an indicator for the monthly income (above/below normal) generated in a cell.

The raw version of our dataset covers all 0.5×0.5 degree cells in Sub-Saharan Africa. However, rioting—by definition—requires human presence, and so we do not expect to observe riots in cells with little population. Our preferred specification thus focuses on

[4] In 2007-08, falling real incomes (induced by a surge in food prices) caused social unrest to flare up in 12 Sub-Saharan African countries (see, e.g., Berazneva and Lee, 2013). According to Demeke et al. (2009), the governments of most of these countries responded by reducing/suspending taxes and tariffs.

[5] By disaggregating our data to the monthly level, we differ from recent contributions (e.g., Harari and La Ferrara, 2013; Hodler and Raschky, 2014) which also use geographically disaggregated data to explore the impact of climate shocks on conflict between organized groups (like rebellions or revolutions). Note, however, that Harari and La Ferrara (2013) perform a temporally disaggregated analysis in the sense that they construct climate indicators for weather conditions during the growing season of the year.

the sample of cells with a population above the 6th decile (evaluated at the country level). Our baseline estimates suggest that a one standard deviation decrease in the SPEI increases the likelihood of rioting by 8.4 percent for the average cell in our restricted sample. If we restrict our sample to cells with a population above the 9th percentile, the corresponding number is 33 percent. Alternative specifications suggest, among other things, that a drop in SPEI has a much larger effect on rioting in cells with a relatively high share of cropland. This finding supports our conjecture that shocks to the water balance affect rioting through agricultural incomes.

This paper is related to a vast empirical literature on the impact of economic shocks, or shocks related to weather anomalies, on violent conflict (Miguel et al., 2004; Burke et al., 2009; Ciccone, 2011). By using a temporally and geographically disaggregated empirical strategy, and by relying on a drought index to proxy for weather anomalies, our work has a particularly close link to recent contributions by Harari and La Ferrara (2013), Couttenier and Soubeyran (2014), and Hodler and Raschky (2014).[6] However, while all these papers focus on big and potentially sustained conflicts between organized groups, our focus here is on riots, i.e., on localized events that flare up spontaneously and tend to die down quickly. Consistent with this pattern, our empirical analysis relies on highly disaggregated data, both in terms of space (we focus on cells of 0.5×0.5 degrees) and in terms of time (we use monthly observations). Other papers considering riots include Hendrix and Salehyan (2012) and Aidt and Leon (2014). The former contribution explores whether deviations from normal rainfall patterns increase the likelihood of various types of disruptive events (including incidents of organized and armed violence, but also including spontaneous events like demonstrations, strikes, and riots). Aidt and Leon (2014), on the other hand, focus on the relationship between rioting and democratic transitions. Both papers, however, rely on yearly observations at the country level.

By emphasizing that negative economic shocks may spark conflict, our theoretical framework is related to models of internal warfare or political transitions. For instance,

[6] A complementary literature explores how enduring structural problems (as distinguished from transitory shocks) affect the incidence of conflict. Part of this literature also relies on subnational data from Africa. Examples include Michalopoulos and Papaioannou (2012) who focus on the consequences of ethnic partitioning; and Besley and Reynal-Querol (2014) who explore the role of historical conflicts.

in the contest models proposed by Chassang and Padro-i-Miquel (2009; 2010) negative transitory shocks on agricultural output decrease the immediate cost of fighting—but not the discounted present value of victory. These models thus predict that groups fight over political power after a negative income shock. Similarly, in Acemoglu and Robinson's (2001) theory of political change, negative shocks may induce democratization because—in bad times—fighting the autocratic regime is relatively cheap.[7] In other dimensions, however, there are stark differences. Our framework does not seek to explain big events like civil wars or democratic transitions. We rather explore the occurrence of smaller events, like riots, which flare up more spontaneously. Therefore, our model does not rely on competing and organized groups of about the same strength, but rather assumes that the authorities clash with unorganized crowds of citizens. In the present framework, the maximum that can be achieved by rioting is to obtain immediate relief through a temporary fall in taxation; a change in the balance of power is out of reach.

The rest of this paper is organized as follows. The upcoming section lays out a simple theoretical model. Section 3 describes our dataset. In Section 4, we present the estimation framework and the empirical results. Section 5, finally, concludes.

2 Theoretical Framework

This section presents a simple theoretical framework providing an economic explanation for why riots emerge in equilibrium and for why the level of rioting fluctuates over time. While we do not test our theoretical framework in a strict sense, it nonetheless motivates the reduced-form empirical model estimated in Section 4. Our theory predicts riots to flare up if a government tries to impose onerous taxation, as has been observed throughout recorded history (see, e.g., Burg, 2004). The framework relies on two key elements. *First*, the government does not immediately observe agricultural output in the different regions of its economy. *Second*, a high level of rioting impedes the collection of taxes, fees, and

[7] In Besley and Persson (2008; 2011), it is positive economic shocks (in the form of higher resource rents) that may lead to conflict because they increase the expected gains from fighting for power. Similarly, in Oechslin (2010), it is an increase in government-controlled rents that may destabilize the regime.

bribes. We will argue that these assumptions are natural in the context of Sub-Saharan Africa, which is the focus of our empirical analysis.

2.1 Assumptions

We consider a region that hosts a set of citizens $N = \{1, ..., n\}$. Time t is discrete and extends to infinity. The citizens derive utility from consumption of a single (non-storable) agricultural good. Consumption by citizen $j \in N$ in period t is denoted by $c_{j,t}$. Period utility is assumed to be linear in consumption (and we can think of the intertemporal utility function as the infinite stream of discounted period utilities).[8] In any period, the region produces a certain amount of an agricultural good (i.e., crop). Agricultural production is either low or high, $Y_t \in \{Y^L, Y^H\}$. The two agricultural output levels are given by $Y^H = z^H \bar{Y}$ and $Y^L = z^L \bar{Y}$, where $\bar{Y}$ denotes the normal (or mean) crop level, $z^H > 1 > z^L$, and $(z^H + z^L)/2 = 1$. Changes in agricultural output are exogenous. We assume that $Y_t = Y_{t-1}$ with probability q and $Y_t \neq Y_{t-1}$ with probability $1 - q$, where q is a measure of output persistence. We impose $q > 1/2$, which implies a positive autocorrelation.[9] The regional agricultural output is spread equally among the population. Hence, citizen i's gross income in t is given by $y_t = Y_t/n$.

The region is subject to taxation by a superior level of government, which is henceforth called the "central government". Taxation should be understood in a broad sense, i.e., to include official taxes and fees, as well as illicit forms of resource diversion. In every period, the central government announces total regional taxation, D_t, which is equally spread among the citizens. As a result, citizen i's announced tax burden in t is given by $d_t = D_t/n$. When deciding on D_t, the government does not observe the current agricultural output, Y_t, but only Y_{t-1}. This assumption appears natural in the context of Sub-Saharan Africa. The World Bank (2005), and more recently Jerven (2013), argue

[8] There is no need to introduce the discount rate formally. As will become clear below, the setup of the model, as well as our focus on Markovian strategies, imply that the game is essentially static.

[9] Note that the analysis presented in Subsection 2.2 is completely unchanged if we allow for trend growth in the normal agricultural output, i.e., if $\bar{Y}_t = (1 + g)\bar{Y}_{t-1}$, where g denotes the growth rate. As we will show below, what matters for rioting is whether the actual agricultural output is below or above the normal agricultural output.

that the lack of unambiguous indicators of economic activity is a key problem in large parts of the continent. Most central governments thus lack the statistical capacity to promptly monitor economic performance across the different (and remote) regions.[10]

The central government's desired level of taxation, D_t, may not always be implemented. We assume that collecting taxes, fees, or bribes is not feasible if the level of rioting is high (because, for instance, the accompanying violence is a threat for the tax collectors). According to Fjeldstad et al. (2014), violent forms of tax resistance have a long tradition in Sub-Saharan Africa, dating back to colonial times. In our framework, the government's ability to enforce D_t depends on two factors, the current level of rioting in the region and the government's current strength. The level of rioting (in practice, this could be the number of days with riots over a certain period) is denoted by

$$R_t = \sum_{j=1}^{n} r_{j,t}, \tag{1}$$

where $r_{j,t}$ refers to citizen j's participation in riot activities. The strength of the central government is reflected by the *i.i.d.* random variable θ_t which is uniformly distributed over $[0, \hat{\theta}(n)]$, with $\hat{\theta}(n)$ increasing in n. By assuming that θ_t fluctuates, we aim to capture that the government is sometimes subject to distracting events (such as power struggles at the national level) that weaken its power in the periphery. To enforce the announced level of taxation, the government must be sufficiently strong: Taxes are enforced if $R_t \leq \theta_t$; otherwise, if $R_t > \theta_t$, the level of rioting makes it impossible to collect any taxes in period t. By conditioning $\hat{\theta}$ on the population size n we capture the fact that a riot is more likely to succeed if a sizeable fraction of population takes part in the riot.[11] Furthermore, we know that the government is more present—and hence stronger—in densely populated regions than in regions with a low population density[12].

[10]See also Mayshar, Moav, and Neeman (2013) who develop a model which, similar to ours, builds on the fundamental assumption that the regional output is not perfectly observed by the central authority. However, while our paper focuses on rioting, Mayshar and coauthors are interested in the consequences of this informational asymmetry for the emergence and the expansion of the state.

[11]More people must participate for a riot to be successful in a more densely populated area: everything else equal, a small number of people rioting in a small village has more impact than in a big city.

[12]From now on we slightly abuse notation and write $\hat{\theta}$ instead of $\hat{\theta}(n)$.

The central government's goal is to tax the region as much as possible—without, however, providing any services to the region. As a result, its period objective function is just given by the current tax revenue (while we can think of the intertemporal objective function as the infinite stream of discounted future tax revenues). The citizens can help avoid taxation by participating in riot activities. Participation is an individual choice and comes at a cost of $e(r_{j,t})y_t$, where e is a strictly increasing and strictly convex function (and $e(0) = e'(0) = 0$). As usual in the literature, the cost depends on y_t to reflect that conflict participation is more costly in periods of strong economic activity (because, e.g., more yield is forgone by the time spent on rioting).

We focus on the (pure strategy) Markov Perfect Equilibrium (MPE), where strategies depend only on the payoff-relevant variables. These consist for the central government of the past agricultural output, Y_{t-1} (since it does not observe the current crop level); and for the citizens of the current agricultural output and the announced level of taxation, Y_t and D_t. The timing of events is as follows. *First*, Y_{t-1} becomes common knowledge and Y_t is privately observed by the citizens. *Second*, the central government announces the level of taxation, D_t. *Third*, the citizens simultaneously decide on their participation in riot activities, $r_{j,t}$, which determines the overall level of rioting, R_t. *Fourth*, the current strength of the central government, θ_t, becomes common knowledge. If $R_t \leq \theta_t$, the announced level of taxation, D_t, is implemented; otherwise, the region escapes taxation.

2.2 Analysis

To obtain explicit solutions, we make specific functional-form assumptions regarding the individual cost associated with participation in riot activities.[13] In particular, we assume that e rises with the square of $r_{j,t}$ (i.e., $e(r_{j,t}) = (r_{j,t})^2$).

To solve the model, we go backwards through an arbitrary period t. Recall that a citizen's strategy can only depend on the two payoff-relevant variables Y_t and D_t. Remember further that Y_t will be disclosed to the central government at the beginning of period

[13] Given the assumptions made in Subsection 2.1, what is required for the results derived below to hold (in qualitative terms) is that the cost function e is "sufficiently" convex.

$t+1$. As a result, the citizens' decisions on $r_{j,t}$ do not alter the government's information set when deciding on D_{t+1}—and hence do not have any implications for subsequent decisions. The maximization of the intertemporal utility function is therefore achieved by maximizing expected current consumption in every single period. The latter is given by

$$E\{c_{j,t}|\,Y_t, D_t\} = (y_t - d_t)\left(1 - F(r_{j,t} + R_{N\backslash j,t})\right) + y_t F(r_{j,t} + R_{N\backslash j,t}) - e(r_{j,t})y_t, \tag{2}$$

where $R_{N\backslash j,t} = \sum_{N\backslash j} r_{j,t}$. Taking into account the functional-form assumptions introduced above, the maximization of $E\{c_{j,t}|\,Y_t, D_t\}$ with respect to $r_{j,t}$ yields $r^*_{j,t} = d_t/(2\hat{\theta}y_t)$.[14] As a result, the level of rioting in the region is given by

$$R^*_t = \sum_{i=i}^{n} r^*_{j,t} = \frac{n}{2\hat{\theta}}\frac{D_t}{Y_t}. \tag{3}$$

So we observe higher levels of rioting if the government announces a higher level of taxation (because then participation in riot activities has a higher expected payoff); or if total agricultural output is lower (because then the individual cost of participation is lower).

Regarding taxation, note that the maximization of the government's intertemporal objective function is—again—achieved through period-by-period maximization. When deciding on current taxes, the government takes the citizens' response, given by (3), into account. So the government's strategy would ideally depend on the current level of the agricultural output. However, the government does not observe Y_t, and so its decision is based on the conditional expectation of Y_t. Formally, the government chooses D_t so as to maximize $E\left\{D_t\left(1 - F(R^*_t)\right|Y_{t-1}\right\}$. The solution to this problem is given by

$$D^*_t = D^*(Y_{t-1}) = \begin{cases} ((\hat{\theta})^2/n)Y^L Y^H (qY^L + (1-q)Y^H)^{-1} & : \quad Y_{t-1} = Y^H \\ ((\hat{\theta})^2/n)Y^L Y^H (qY^H + (1-q)Y^L)^{-1} & : \quad Y_{t-1} = Y^L \end{cases}. \tag{4}$$

Since $q > 1/2$, it follows that $D^*(Y^H) > D^*(Y^L)$: If the previous agricultural output was

[14] This result requires $d_t/y_t \leq 2(\hat{\theta})^2/n$. If this condition were violated, we would have $r^*_{j,t} = \hat{\theta}/n$, implying that the government would fail with certainty to enforce the announced level of taxation. The results derived below suggest that this condition always holds if $Y_H/2 \leq qY_L + (1-q)Y_H$, which is henceforth assumed (just to avoid a distinction of cases that would not add any additional insights).

above the normal level, the central government's expectation of the current agricultural output—and hence the expected cost of riot activities—is also relatively high. As a result, the citizens' incentives to participate in riot activities are expected to be weak—which induces the central government to announce a relatively high level of taxation.

We now combine the best responses of the citizens (equation 3) and the central government (equation 4) and arrive immediately at the following results:

Proposition 1 *The equilibrium level of rioting depends on the deviations of the past and the current agricultural output from the normal one. Using $z_t = Y_t/\bar{Y}$, we obtain:*

$$R_t^* = R^*(z_{t-1}, z_t).$$

There are four different levels of rioting, which can be ordered as follows:[15]

$$R^*(z^L, z^H) < R^*(z^H, z^H) < R^*(z^L, z^L) < R^*(z^H, z^L).$$

The ranking in Proposition 1 implies that rioting is at its highest level if Y^L is preceded by Y^H. Why? As discussed following equation (4), the observation of an above-normal agricultural output level in $t-1$ makes the central government announce relatively high taxes in t. So, if the current crop level turns out to be below-normal, instead of above-normal as expected, the government tries to impose heavy taxation in a situation where participation in riot activities is cheap. The result of this must be a high level of rioting. On the other hand, rioting is at its lowest level if Y^H is preceded by Y^L. In this constellation, the government's current taxation plans are just modest, while the cost of participating in riot activities is high. Finally, if there is no change in agricultural output, the level of rioting is intermediate as the announcement of relatively high (low) taxes coincides with a relatively high (low) cost of participation.[16] In sum, it is the fact that

[15] The four levels of rioting are given by $R^*(z^H, z_t) = (\hat{\theta}/2)(z^L z^H/z_t)(qz^L + (1-q)z^H)^{-1}$ and $R^*(z^L, z_t) = (\hat{\theta}/2)(z^L z^H/z_t)(qz^H + (1-q)z^L)^{-1}$, where $z_t \in \{z^L, z^H\}$.

[16] We have $R^*(Y_H, Y_H) < R^*(Y_L, Y_L)$ because, if $Y_{t-1} = Y_L$, there is a chance that the output increases between $t-1$ and t, which makes the government announce relatively high taxes (as compared to a situation in which $Y_t = Y_L$ is certain). Hence the relatively high level of rioting if $Y_{t-1} = Y_t = Y_L$.

the central government sometimes misjudges the region's economic situation that leads to fluctuations in rioting.

2.3 From Theory to Evidence

Proposition 1 suggest a simple contemporaneous relationship between the level of rioting and the deviation of the actual agricultural output from its normal level:

Conjecture 1 *Other things equal, as illustrated by Figure 1, we should observe that the regional level of rioting (e.g., the number of days with riots over a certain period) is:*

- *Relatively high if the actual agricultural output is less than the normal output;*
- *Relatively low if the actual agricultural output is greater than the normal output.*

The relationship is less strong in less densely populated regions.[17]

Section 4 explores whether such a negative and immediate impact of agricultural output deviations can be identified in Sub-Saharan Africa. To do so, we use monthly data and interpret subnational cells of 0.5×0.5 degrees as regions. Motivated by Conjecture 1, our baseline regression equation relates the level of rioting in a given cell and month to a measure of the monthly deviation of the actual from the normal cell output. This disaggregated approach is tailored to the frequent and localized nature of the phenomenon. Unlike conflicts between organized groups, which are usually measured as binary responses at higher levels of geographical and temporal aggregation, riots flare up immediately in response to a stimulus (e.g., onerous taxation), are short-lived, occur multiple times in a year, and are usually confined to the region affected by the stimulus.

Figure 1 here

[17] The slope of the line in Figure 1 is given by $-2\hat{\theta}(n)q(1-q)(1-(z^H-1)^2(2q-1))^{-1}$, implying that the relationship is more pronounced when $\hat{\theta}(n)$ and z^H take higher values; and when q is closer to 1/2.

To uncover any possible causal effect of agricultural output fluctuations on the level of rioting, we need to address a number of issues. Most importantly, there are a two econometric problems that make it difficult to identify causal effects in our context. *First*, cell output could be endogenous in the sense that—although not modeled in the theoretical framework—there may be forces affecting crop level and rioting simultaneously. Such forces may be time-varying and related to regional developments (e.g., an inadequate response by the central government to a regional natural disaster) or to national developments (e.g., an unpopular change in national economic policies that is costly to the region). Moreover, we cannot rule out that there are time-invariant cell characteristics (e.g., the terrain) that affect both output and unrest. *Second*, there could be problems of reverse causality as the level of rioting may have an impact on economic activity. If the empirical measure of cell output reflects output net of rioting costs, $(1 - e(R_t/n))Y_t$, an exogenous surge in the level of rioting (e.g., due to a spike in ethnic tensions) reduces measured cell output. *Finally*, there is an issue of data availability. Following a geographically and temporally disaggregated approach, the required output data is not available.

We deal with all of these issues by means of our set of explanatory variables. We control for any time-invariant cell-characteristics by using cell fixed-effects. We further include region-by-month and country-by-year fixed-effects to account for time-varying confounding factors as much as possible (including any seasonal patterns). To proxy for deviations of the actual agricultural output from the normal output, we use the Standardized Precipitation-Evapotranspiration Index (SPEI) constructed by Vicente-Serrano et al. (2010). Section 3 below argues in detail why the SPEI is a well-suited proxy in our context. In brief, SPEI is a drought index that reflects a cell's climatic water balance. An index value greater (less) than zero indicates an above-normal (below-normal) water balance. As a result, there is a positive association between SPEI and the deviation of agricultural productivity—and hence agricultural output—from its normal level. So, in line with much of the related conflict literature (e.g., Burke et al., 2009; Harari and La Ferrara, 2013; Couttenier and Soubeyran, 2014), we perform a reduced-form analysis. Relying on SPEI is also a way of addressing any omitted variables and the reverse-causality problem: Apart from the time-invariant factors such as latitude, SPEI is constructed from weather information only—and is therefore strictly exogenous. That is, random fluctuations in weather are independent of any other potentially confounding factor. Moreover, the level of rioting has no impact on weather and therefore reverse causality is not an issue when using SPEI. Finally, to explore whether a possible effect of SPEI on rioting works through the agricultural output channel, we estimate additional specifications which interact SPEI with a measure of the share of the cropland in the cell.

To sum up, our baseline regression equation to be estimated in Section 4 is given by

$$R_{it}^{*} = \alpha + \beta SPEI_{it} + \gamma_i + \delta_{rm} + \rho_{cy} + \varepsilon_{it}, \tag{5}$$

with i and t standing for cell and month, respectively. As in the theoretical framework, R_{it}^{*} is a measure of the level of rioting. γ_i refers to cell (i) fixed effects, while δ_{rm} and ρ_{cy} denote, respectively, the region-by-month (r and m) and the country-by-year (c and y) fixed effects (with the regions being Eastern, Western, Southern, and Middle Africa). The parameter of interest in specification (5) is β, which is predicted to have a negative sign by Conjecture 1. Conjecture 1 also predicts that this relation should be stronger in more populated area. Assuming that the impact of SPEI works through the output channel, we further expect the SPEI-cropland share interaction (not shown in 5) to enter negatively. Given the structure and the size of the dataset (long panel with more than 2,000,000 observations), we employ linear panel estimation throughout. That is, we follow the recent conflict literature (e.g., Harrari and La Ferrara, 2013; Hodler and Raschke 2014) in relying on linear estimation even when we rely on binary dependent variables.

3 Data

3.1 Data Sources and Descriptive Statistics

Our empirical analysis relies on several data sources. The information used to construct our dependent variable stems from the Social Conflict in Africa Database (SCAD). SCAD lists different types of social unrest (like strikes, demonstrations, or riots) starting from 1990 for all African countries with a population size of more than one million. The database was compiled by Hendrix and Salehyan and is based on newswires from Associated Press and Agence France Presse.[18] The data are geo-coded and contain detailed information on, among other things, event type and duration. SCAD does not include, however, violent events that are directly related to armed internal conflicts. Such events are covered by the PRIO/Uppsala ACLED dataset, i.e., by the data source that is typically used in the related conflict literature. The type of unrest events we consider here are riots. Broadly consistent with the role of rioting in our theoretical framework, a riot is defined by SCAD as a "distinct, continuous, and violent action" directed toward government authorities (or toward members of a distinct "other" group). We construct three different dependent variables at the cell-month level. The first two variables, NoD and Inc, are measures of the level of rioting. NoD is a count variable that gives the number of days with riots; it is the measure that most closely mirrors its theoretical counterpart, R^*_{it}. Inc reflects riot incidence; it is a binary variable that equals one if we observe at least one riot. The third dependent variable, Ons, reflects riot onset; it is a binary variable that equals one if we observe at least on riot in t, but none in $t-1$. The two binary dependent variables are often used in the related conflict literature.

The main explanatory variable is an agriculture-relevant drought index, the so-called Standardized Precipitation-Evapotranspiration Index (SPEI) which was developed by Vicente-Serrano et al. (2010). SPEI reflects the climatic water balance at different time scales. We consider the monthly climatic water balance, i.e., the monthly difference between precipitation and potential evapotranspiration. The climatic water balance is an important factor affecting vegetation activity and, as a result, agricultural productivity. According to Vicente-Serrano et al. (2012), the correlation between the water balance and vegetation activity is particularly strong and immediate under arid, semi-arid, and sub-humid conditions, i.e., under conditions one finds in many parts of Africa's agricultural regions. Moreover, in many African countries, production at the farm level is highly

[18] The database can be accessed through the website *www.sca ddata.org*. See the codebook, which is posted on the website, for a full description of the database.

diversified in terms of crops (see, e.g., Chavas and Di Falco, 2012). The growing and harvest season therefore tends to cover a large part of the year, implying that moisture conditions matter throughout the year as well. Importantly, SPEI is a standardized variable. It expresses the climatic water balance in units of standard deviations from the long-run average (which is calculated over the 1901-2012 period). A value of zero means that the water balance is exactly at its long-run average; a value of plus one (minus one) means that the water balance is one standard deviation above (below) the long-run average, etc. This standardization, and the fact that the water balance matters for agricultural productivity throughout the year, make the index particularly well suited for the present context: Deviations of SPEI from zero can be interpreted as deviations of the actual agricultural output from the normal agricultural output; moreover, given that the agricultural sector has a significant weight in Sub-Saharan economies, SPEI can also be regarded as a proxy for deviations of the actual total output from its normal level.[19]

By using a drought index, instead of just rainfall and/or temperature, we follow some of the more recent papers on climate and conflict (e.g., Harari and La Ferrara, 2013; Couttenier and Soubeyran, 2014). One of the concerns with rainfall as such is that it is not a priori clear how and to what extent precipitation affects agriculture. For instance, the impact of precipitation on agriculture depends also on the degree to which water is retained by the soil. The capacity of the soil to retain water, in turn, depends on a variety of factors, including most notably surface temperature, but also air humidity, sunshine exposure, latitude, and wind speed. Drought indices like SPEI or PDSI (which is used by Couttenier and Soubeyran, 2014) incorporate this information. We chose to use SPEI because of its higher level of disaggregation. Given that we consider riots (which are more frequent and more localized than conflicts between organized groups), the high level of spatial and temporal disaggregation is an important part of our empirical strategy.

Next to relying on SCAD and the SPEI database, we work with a variety of other

[19]In the average Sub-Saharan economy, agricultural output accounted for about one third of the GDP in 1990 and for about one fourth in 2010, according to data from the World Development Indicators (http://data.worldbank.org/data-catalog/world-development-indicators). For the year 1990, FAO data (http://faostat.fao.org) classifies about 65% of the total population in Sub-Saharan Africa as agricultural population (for the year 2010, the corresponding number is 55%).

information sources. We use data on population sizes from the PRIO-GRID project (Tollefsen et al., 2012). We need population data because—following the prediction of Conjecture 1—we restrict our empirical analysis to areas with a certain population density (see the following subsection). We also use data on the share of crop areas in each cell (Ramankutty et al., 2008) to explore whether the impact of the SPEI on riots works through deviations of the actual agricultural output from the normal one, as described in Subsection 2.3. Finally, we use the relevant United Nations Statistics Division classification to assign each 0.5×0.5 degree cell to a Sub-Saharan region, which allows us to construct the region-by-month fixed effects. Table 1 provides summary statistics for the main variables used in the later empirical analysis.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
NoD	0.002046	0.15998	0	31	2006120
Inc	0.000753	0.027434	0	1	2006120
Ons	0.000655	0.025594	0	1	2006120
SPEI	-0.163	0.996	-8.506	6.68	1910722
Pop	76696.532	190084.118	0	5399045.5	2001571
Crop	0.083	0.138	0	1	1977080

Note: Summary Statistics for the full sample. NoD: number of days with riots; Inc: binary indicator that equals one if at least one riot is observed; Ons: binary indicator that equals one if at least on riot is observed in t, but none in t - 1; SPEI: Standardized Precipitation-Evapotranspiration Index; Pop: population size; Crop: share of land used for growing crops or pasture; GDPpc: GDP per capita.

3.2 Geographical Characteristics of Rioting

Conjecture 1 predicts that the relation between agricultural output and rioting should be stronger in more densely populated area. Many regions in Sub-Saharan Africa are characterized by types of land that are hostile to human settlement (e.g., deserts, regularly flooded areas, or dense forests). These regions typically show a low populations density. Thus, for our analysis, we group cells according to the population distribution for each country and focus on cells in which the population is greater than the population at a specific decile of the relevant country's distribution. Table 2 shows some descriptive

Table 2: Descriptive Statistics based on population deciles

Decile	N (cells)	Rioting	SPEI	Cropland	Population
1	6,810	.971542	-.15655722	.08757274	11221
2	6,062	.9569821	-.1516641	.09185871	16194
3	5,294	.943084	-.1424928	.09699274	21706
4	4,549	.9285241	-.13848273	.10282339	28095
5	3,802	.8762409	-.13378653	.1098709	37054
6	3,034	.8232958	-.12856168	.11767683	51319
7	2,278	.7372601	-.12379031	.12722936	72006
8	1,518	.6512243	-.1154652	.1386438	105547
9	756	.5201853	-.10765097	.15088922	172342

Note: The different rows show summary statistics for various variables when restricting the sample to cells with a population greater than the population at certain deciles (listed in Column 1) of the relevant country's distribution. Column 2 indicates the number of observations that are left when focusing on cells with a population above a specific decile. Column 3 shows the share of observations with at least one riot that are covered by the restricted sample. Column 4 indicates the average SPEI for the restricted sample. Column 5 contains the average percentage of cropland in the restricted sample and Column 6 shows the average population sizes of the cells that are at the respective decile.

statistics for cells which are, respectively, above the 1st, the 2nd, $\cdots$, and the 9th decile.

Column 2 of the table shows that more than 82 percent of all observations with at least one riot are covered by cells with a population greater than the population at the 6th decile of the relevant country's distribution. When we take the 9th decile as the threshold, the corresponding number is still 52 percent. It can also been seen that the average share of cropland increases with the size of the population. While only an average of around 9 percent of the overall cell area is cropland when we exclude cells in the 1st decile, more than 15 percent on average is used for growing crops when we focus on cells above 9th decile. Evidently, being restrictive in terms of population size comes at the cost of loosing a substantial share of cells and—to a lesser extent—also of loosing riots. In the following empirical analysis, we therefore focus on cells with a population greater than the population at the 6th decile of the relevant country's distribution. In doing so, we still cover more than 82 percent of all observations with at least one riot. Imposing this restriction implies that the share of observations with at least one riot rises from 0.08 to 0.16 percent, while the share of cells with at least one riot (over the entire period) rises from 6.7 to 12.3 percent. At the same time, the average share of land used for growing crops increases from less than 9 percent to about 12 percent.

4 Results

Table 3 shows the results for the baseline specification when we restrict our sample to cells with a population above the 6th decile (evaluated at the country level, as described in Section 3).[20] The differences in the estimates between the alternative specifications (Columns 1–3, 4–6, and 7–9) stem from the use of different sets of fixed effects as indicated by the lower half of Table 3. As described in Subsection 2.3, γ_i, δ_{rm}, and ρ_{cy} stand for cell, region-by-month, and country-by-year fixed effects, respectively (see also the notes at the bottom of the table). Table 7 in the Appendix displays results based on alternative population restrictions. We discuss them briefly at the end of this section.

The signs of the parameter estimates for SPEI are negative throughout, as predicted. In particular, consistent with the theory, there is a significant negative relationship between SPEI and the level of rioting: When we use Inc, the binary measure, as a proxy for the level of rioting, the relationship is highly significant; when we rely on NoD, the count measure, the relationship is at least marginally significant (note that the vast majority of rioting incidences in our dataset—85%—only last for a week or less). We further observe that a drop in SPEI has a highly significant impact on the onset of riots. In terms of magnitude, the estimates in Table 3 suggest that a one-standard-deviation decrease in SPEI increases the probability of observing a riot in a given cell and month by 8.4 percent for the average cell in our restricted sample.[21] Similarly, a one-standard-deviation decrease in SPEI translates in an increase in the number of days with riots in a given cell and month of 10.3 percent. This implies a rather substantial effect when calculated at the yearly level—assuming that the change in the SPEI would be constant throughout the year and for all cells.

One obvious extension of the baseline specifications is the analysis of potential inter-

[20]However, as a robustness check we also estimated an identical specification when evaluating the 6th decile for the entire Sub-Saharan Africa. The results are very similar and are available from the authors upon request.

[21]A one standard deviation below the mean in the SPEI increases the likelihood to observe a riot in a cell in a month by 0.0126 percentage points. The unconditional probability of having a riot in a cell (with population above the 6th decile) in a month is 0.0015. A drop of one standard deviation in the SPEI thus increases the likelihood of having a riot on the average cell by around 8.4%.

Table 3: Baseline specifications

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
SPEI	-0.000384 (0.108)	-0.000126 (0.011)	-0.000130 (0.004)	-0.000379 (0.110)	-0.000124 (0.013)	-0.000129 (0.004)	-0.000440 (0.053)	-0.000128 (0.008)	-0.000130 (0.004)
N	783285	783285	783285	783285	783285	783285	783285	783285	783285
NoG	2977	2977	2977	2977	2977	2977	2977	2977	2977
T_{min}	25	25	25	25	25	25	25	25	25
T_{mean}	263.1	263.1	263.1	263.1	263.1	263.1	263.1	263.1	263.1
T_{max}	264	264	264	264	264	264	264	264	264
γ_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
δ_{rm}	Yes	Yes	Yes				Yes	Yes	Yes
ρ_{cy}	Yes	Yes	Yes	Yes	Yes	Yes			
δ_m				Yes	Yes	Yes			
ρ_y							Yes	Yes	Yes

Note: p-values in parentheses. Standard errors are clustered at the cell level. NoD: number of days with riots; Inc: binary indicator that equals one if at least one riot is observed; Ons: binary indicator that equals one if at least on riot is observed in t, but none in t - 1; N: number of observations; NoG: number of cells; T_{min}, T_{mean}, and T_{max}: minimum, mean, and maximum number of months available for all cells in the sample. γ_i: cell fixed effects; δ_{rm}: region-by-month fixed effects; ρ_{cy}: country-by-year fixed effects; δ_m: month fixed effects; ρ_y: year fixed effects.

actions effects. In particular, we suspect the impact of SPEI on rioting to be stronger in areas with a higher agricultural activity (because of a stronger link between SPEI and total cell output in agricultural areas). Table 4 presents several specifications testing for the presence of such effects. Columns 1–3 show results when an interaction SPEI×Crop is included, where Crop is a dummy that equals one if the share of cropland is above the median; in Columns 4–6, the interaction term is SPEI×Pop8, where Pop8 is a dummy that equals one if the population is above the 8th decile (note that the sample is restricted to only include cells with a population above the 6th decile). Finally, columns 7–9 account for the two interactions simultaneously. The reason for including columns 4–6 and 7–9 is the positive correlation between population size and the share of crop area as shown in Table 2. Hence, columns 4–6 confirm that there is a larger effect in more densely populated areas even when using the restricted sample (see also Table 7 in the appendix). Columns 7–9 confirm that the interaction effect for SPEI×Crop remains economically and statistically significant even when accounting for an interaction effect between SPEI and Pop8. That is, the interaction effect between SPEI and the share of cropland is not

Table 4: Interaction effects

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
SPEI	-0.00017	-0.000027	-0.000032	-0.000241	-0.000032	-0.000039	-0.000073	0.000042	0.000034
	(0.554)	(0.447)	(0.359)	(0.398)	(0.437)	(0.337)	(0.832)	(0.367)	(0.446)
×Crop	-0.000311	-0.000146	-0.000144				-0.000271	-0.000119	-0.000118
	(0.431)	(0.054)	(0.042)				(0.481)	(0.090)	(0.078)
×Pop8				-0.000292	-0.000194	-0.000186	-0.000257	-0.000178	-0.000171
				(0.530)	(0.043)	(0.038)	(0.577)	(0.054)	(0.052)
N	783285	783285	783285	783285	783285	783285	783285	783285	783285

Note: p-values in parentheses. All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects. Crop and Pop8: are dummies variables for cells with, respectively, an above-median share of cropland and a population above the 8 decile. See Table 3 for additional information.

spurious in the sense that the estimates for SPEI×Crop only reflect the effects of a larger population in agricultural areas.

Focusing on the results for riot incidence (Ins) and onset (Ons), both interaction terms (SPEI×Crop and SPEI×Pop8) are statistically significant. The estimates for the level of SPEI become insignificant and much smaller. More specifically, we see a 16 percent increase in the estimates when introducing the SPEI-cropland interaction (columns 1–3)[22] and 54 percent increase when introducing the SPEI-population interaction (columns 4–6).[23] The estimates for both interaction terms decrease slightly in terms of size but they remain statistically significant in the joint specification (columns 7–9). The empirical findings shown in Table 4 hence confirm that—consistent with our initial conjectures—a drop in SPEI has a larger effect on rioting in areas whith a higher agricultural activity.

Table 5 in the Appendix shows results when we control for the potential persistence of the dependent variable and for lagged effects of SPEI.[24] According to Columns 1–3 and 7–9, the inclusion of various lags of the dependent variable does not change the estimated

[22]This pattern remains when we investigate the interaction further. E.g., using 4 interaction terms instead of one, i.e. dividing Crop into 4 categories (-25th, 25th-50th, 75th+ percentile), we find negative and significant effects for both categories above the median and no significant effect below the median.

[23]Table 7 in the appendix provides a more detailed analysis for different sample restrictions. The results in Table 7 are very much in line with columns 4–6 in the sense that there is a monotonic relationship between population size and the effect of SPEI on rioting. In particular, the effect of SPEI on rioting is strictly increasing with population size.

[24]Given the long time dimension of our dataset (263 month on average) we employ standard fixed-effects regression as the Nickell (1981) bias is negligible in our case.

impact of SPEI by much (in absolute terms, the point estimates turn slightly bigger). However, a difference worth noticing concerns the statistical significance of the estimates relying on NoD, our count measure, as the dependent variable. While the estimated impact of SPEI on NoD is only marginally significant in Table 3, it is highly significant when we introduce lagged values of NoD. Similarly, the inclusion of lagged values of SPEI does not affect substantially the estimated contemporaneous impact of SPEI on rioting (Columns 4-6). As for the lagged effects of SPEI, no clear picture emerges.

Tables 6 and 7 in the Appendix display the results of several robustness checks, including first-differencing and changing the sample restriction. The results based on the standard first-differenced (fd) specification, shown in Columns 1–3 of Table 6, bring again a confirmation of the baseline results. The fd-estimates are just slightly more significant, both in economic and statistical terms. Moreover, when we relate the level of rioting, or riot onset, to changes in SPEI (i.e., $SPEI_t - SPEI_{t-1}$), we also tend to find a significant negative relationship (see Columns 4–6 of Table 6). Consistently with Conjecture 1, we can see in Table 7 that, overall, being more restrictive in terms of population leads to higher parameter estimates (in absolute terms), indicating a stronger effect of SPEI. For instance, when we include all cells above the 5th decile, a one-standard-deviation decrease in SPEI rises the likelihood of observing at least one riot by 7 percent in the average cell; when only cells above the 9th decile are included, the corresponding number is 33 percent.

Finally, Table 8 in the Appendix reports results for different types of standard errors. So far, all standard errors have been clustered at the cell level. However, given the precision of our data in terms of both space and time (with an average of 263 month in our sample), different forms of spatial dependence and autocorrelation may affect standard errors. Columns 1–3 of Table 8 therefore report results based on standard errors that are robust to spatial and temporal dependence (Driscoll and Kraay, 1998). Columns 4–6 display results for classical heteroscedasticity and autocorrelation consistent (HAC) standard errors (Newey and West, 1994), while the estimates in Columns 7–9 are based on standard errors that are robust to arbitrary intra-group autocorrelation (Kiefer, 1980). As can be seen from the table, our baseline results are highly robust to changes in the type of standard errors used.

5 Conclusions

Anecdotal evidence suggests that violent riots, which are a widespread phenomenon in poorer economies, disrupt commerce and basic government functions. Frequent outbursts of riots are therefore a serious obstacle to economic growth in developing countries. Our data from Sub-Saharan Africa suggest further that riots are also costly in terms of human lives. Over the 1990–2012 period, the average riot was associated with 66 fatalities. Although riots matter, the internal-conflict literature has so far almost exclusively focused on explaining conflict between organized groups, such as coups, rebellions, or revolutions. This paper, by contrast, explores some possible triggers of riots. Our theoretical framework predicts a negative relationship between the level of rioting and the deviation of the actual output from its normal one: Riots flare up in response to a deterioration of a region's economic situation because the central government is slow in lowering the tax burden; put differently, in the framework, riots are triggered by onerous taxation. Our empirical analysis, which relies on highly disaggregated data (monthly, 0.5×0.5-degree cells), indeed suggests that the level or rioting is high (low) if the actual output is below (above) the normal one. As monthly output data at such a high spatial resolution is unavailable, we use the SPEI drought index—which can be viewed as an indicator of agricultural productivity—to proxy for deviations of the total output from normal levels. We find that a one-standard-deviation decrease in SPEI rises the likelihood of a riot in a given cell and month by 8.4 percent. We further find larger effects in cells with an above-median share of cropland. This finding substantiates the conjecture that SPEI affects the level of rioting through the (agricultural) output channel.

By exploring the triggers of violent riots, the present paper gives also rise to a number of new questions that will be interesting to address. For instance, anecdotal evidence suggests that "big" events like rebellions or revolutions are often preceded by periods with high levels of rioting (while, of course, not all periods with high levels of rioting are followed by rebellions or revolutions). So an obvious question would be whether we find such correlations in the data. Similarly, it would be important to have a model that would allow us to explore the circumstances under which a series of riotst is more likely to escalate into a full-blown rebellion or revolution. Addressing these questions would help to fill the void between research on rioting and the literature on conflict between organized groups. At the moment, we leave these questions to future research.

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Appendix

Table 5: Estimation results including lags of the dependent variables and SPEI

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
DV,									
lag 1	0.411	0.0790	-0.0355				0.418	0.0830	-0.0356
	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
lag 2	0.0166	0.0226	0.0226						
	(0.630)	(0.005)	(0.005)						
lag 3	-0.00480	0.0207	0.0207						
	(0.797)	(0.003)	(0.003)						
SPEI,	-0.000510	-0.000142	-0.000139	-0.000405	-0.000145	-0.000147	-0.000488	-0.000130	-0.000131
	(0.018)	(0.006)	(0.003)	(0.088)	(0.005)	(0.002)	(0.024)	(0.010)	(0.004)
lag 1				-0.000071	0.000088	0.000091			
				(0.739)	(0.079)	(0.057)			
lag 2				-0.000347	-0.000107	-0.000081			
				(0.217)	(0.009)	(0.047)			
lag 3				-0.000456	-0.000028	-0.000023			
				(0.033)	(0.496)	(0.568)			
N	774241	774241	774241	771215	771215	771215	780270	780270	780270

Note: p-values in parentheses. Standard errors are clustered at the cell level. NoD: number of days with riots; Inc: binary indicator that equals one if at least one riot is observed; Ons: binary indicator that equals one if at least on riot is observed in t, but none in t - 1; N: number of observations; All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects.

Table 6: Estimation results for first-differenced specifications

	NoD, fd	Inc, fd	Ons, fd	NoD	Inc	Ons
SPEI, fd	-0.000471	-0.000191	-0.000189	-0.000140	-0.000108	-0.000111
	(0.035)	(0.005)	(0.004)	(0.326)	(0.006)	(0.004)
N	779253	779253	779253	779253	779253	779253

Note: Columns 1–3 present results for the first-differenced specification excluding cell fixed effects (γ_i), but including region-by-month (δ_{rm}) and country-by-year (ρ_{cy}) fixed effects. Columns 4–6 display estimates for the baselines specification including the full set of fixed effects, but using the first difference of SPEI ($SPEI_{it} - SPEI_{it-1}$) instead of the level.

Table 7: Estimation results for different sample restrictions

	NoD	NoD	NoD	NoD	NoD	Inc	Inc	Inc	Inc	Inc
SPEI	-0.000252	-0.000384	-0.000481	-0.000738	-0.00112	-0.0000908	-0.000126	-0.000162	-0.000242	-0.000434
	(0.190)	(0.108)	(0.072)	(0.057)	(0.086)	(0.027)	(0.011)	(0.011)	(0.008)	(0.009)
N	978468	783285	590636	393052	197292	978468	783285	590636	393052	197292
Decile	5	6	7	8	9	5	6	7	8	9

	Ons	Ons	Ons	Ons	Ons
SPEI	-0.0000995	-0.000130	-0.000168	-0.000250	-0.000412
	(0.008)	(0.004)	(0.004)	(0.002)	(0.005)
N	978468	783285	590636	393052	197292
Decile	5	6	7	8	9

Note: p-values in parenthesis. Standard errors are clustered at the cell level. NoD: number of days with riots; Inc: binary indicator that equals one if at least one riot is observed; Ons: binary indicator that equals one if at least on riot is observed in t, but none in t - 1; N: number of observations; Decile: population threshold (referring to the country-level distribution) above which a cell is included in the sample. All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects.

Table 8: Estimation results for different types of standard errors

	NoD	Inc	Ons	NoD	Inc	Ons	NoD	Inc	Ons
SPEI	-0.000436	-0.000122	-0.000127	-0.000436	-0.000122	-0.000127	-0.000436	-0.000122	-0.000127
	(0.074)	(0.034)	(0.022)	(0.094)	(0.004)	(0.001)	(0.062)	(0.010)	(0.005)
N	783285	783285	783285	783285	783285	783285	783285	783285	783285

Note: *p*-values in parenthesis. All specifications include cell (γ_i), region-by-month (δ_{rm}), and country-by-year (ρ_{cy}) fixed effects. Columns 1–3 report specifications using standard errors that are robust to spatial and temporal dependence (Discroll and Kraay, 1998). Columns 4–6 show results for heteroscedasticity and autocorrelation consistent (HAC) standard errors (Newey and West, 1994). Finally, Columns 7–9 display specifications based on standard errors that are robust to arbitrary intra-group autocorrelation (Kiefer, 1980).